ENHANCING SKIN CANCER DIAGNOSIS WITH EXPLAINABLE AI

Nipun Sandamal, Dr Ing. Stefania Cristina, Prof. Ing. Kenneth P Camilleri
Department Of Systems And Control Engineering

1 BACKGROUND

1.1 INTRODUCTION

Traditional skin cancer diagnosis is invasive and time-consuming. Non-invasive computer vision methods using deep neural networks offer faster results on diverse thermoscopic data [1] [2]. But without explainability, can dermatologists trust these AI-driven predictions for clinical decisions?

1.2 AIM

To leverage computer vision methods with explainability and interpretability to analyze three imaging modalities: thermography, hyperspectral imaging, and dermoscopy.

1.3 OBJECTIVE

1. Train neural networks on dermoscopic data that produce results aligned with human reasoning in image classification.
2. Investigate how combining thermography and hyperspectral imaging can enhance prediction precision, while collaborating with dermatologists to evaluate the model's explain ability and performance.

2 METHODOLOGY

1. Model of choice is a prototype network [3] with an architecture shown in Figure: 1.

2. Prototype network can be break down into following components:

- **BackBone**
  - A pre-trained vanilla CNN such as ResNet18 or VGG19.
  - Responsible for extracting high-level features from the input image.
- **Prototype Layer**
  - Contains a set of prototypes for each class.
  - Functions like filters in a traditional CNN, but instead of computing dot products with feature maps, it measures the similarity between each prototype and every patch of the image.
- **FC Layer**
  - A linear layer that outputs a logit for each class in the dataset.
  - Provides a measure of how strongly a given prototype is connected to each class.

4. Prototypes can be considered representative samples for each class in the dataset. These prototypes are learned during model training and must be medically relevant. Each prototype for a given class should uniquely capture a distinctive pattern associated with that class.

$$\text{sim}(z, p_j) = \text{avg top-}k_{\tilde{z} \in Z_a} \log \frac{\|\tilde{z} - p_j\|_2 + 1}{\|\tilde{z} - p_j\|_2 + \epsilon}$$

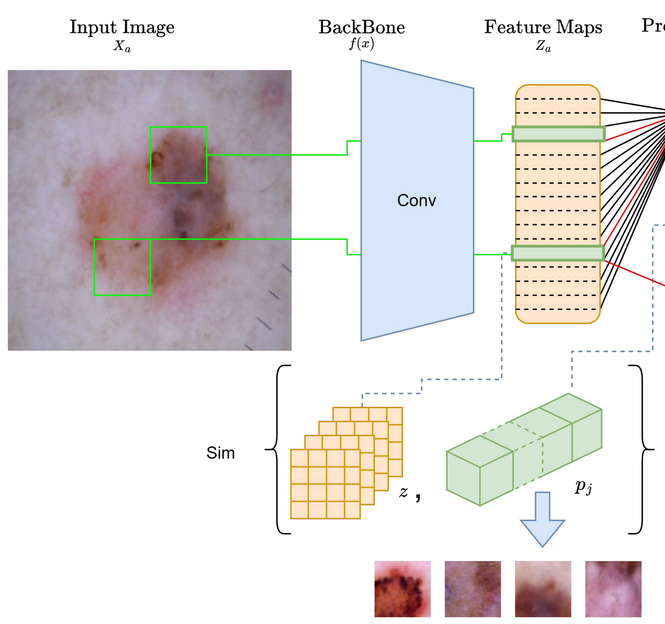

Figure: 1

2.1 TRAINING OF THE PROTOTYPE NETWORK

Prototypes from the same class should be closely clustered together, while prototypes from different classes should be distinctly separated. This optimization can be formulated as follows:

$$L_{\text{clst}} = \min_{p_j \in P_{y_a}} \min_{z \in Z_a} \|z - p_j\|_2$$

$$L_{\text{sep}} = - \min_{p_j \notin P_{y_a}} \min_{z \in Z_a} \|z - p_j\|_2$$

3 RESULTS & DISCUSSION

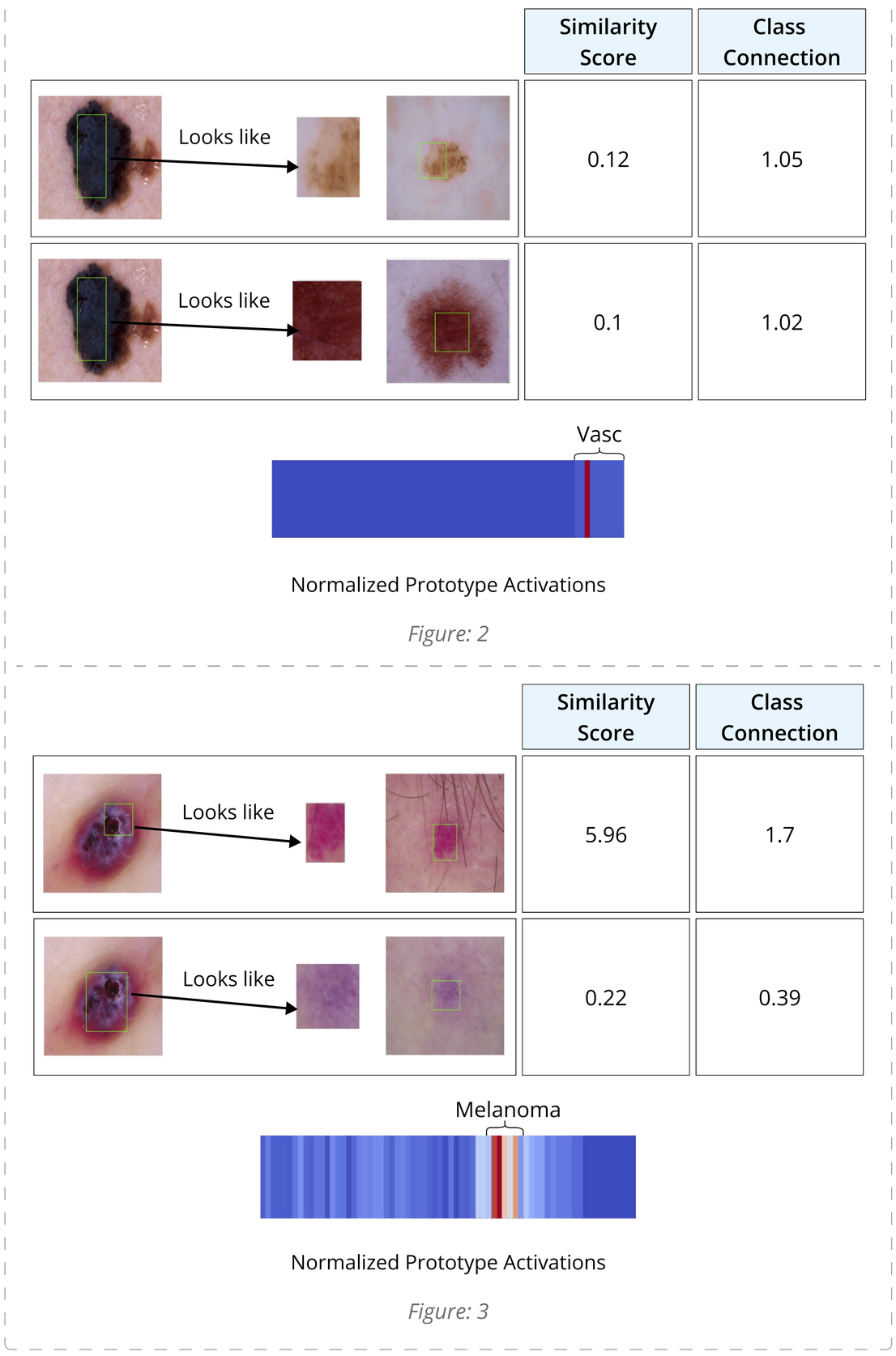

Figure: 2

Figure: 3

The model was trained on the HAM10000 dataset, achieving 98% accuracy on the training set and 84% accuracy on the testing set.

Pros	Cons
1. As shown in Figure: 3 in the melanoma heatmap activation, only the melanoma prototypes exhibited the highest activation. 2. In some cases, there is very high activation for a specific prototype within a particular class, as shown in Figure: 2	1. Prototypes can sometimes represent confounding factors such as hair, markers, or the boundaries of skin lesions. 2. Even though prototypes exhibit high activation, it is doubtful whether they are medically relevant.

4 FUTURE WORK

1. Incorporating dermatologist validation into prototype networks.
2. Exploring the use of alternative backbone networks such as Capsule Networks.
3. Training and testing the model on thermal and hyperspectral data.

5 REFERENCES

1. Gouda, Niharika, and J. Amudha. "Skin cancer classification using ResNet." 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA). IEEE, 2020
2. Tabrizchi, Hamed, Sepideh Parvizpour, and Jafar Razmara. "An improved VGG model for skin cancer detection." Neural Processing Letters 55.4 (2023): 3715-3732.
3. Chen, Chaofan, et al. "This looks like that: deep learning for interpretable image recognition." Advances in neural information processing systems 32 (2019).